NEURAL INFORMATION PROCESSING SYSTEMS

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THE FIN AI

MetaAligner: Towards Generalizable Multi-Objective Alignment of Language Models

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Multi-Objective Alignment of LLMs

- Alignment of Large Language Models (LLMs)
  - Target: Generating high-quality responses that align with human expectations and values;
  - Objectives: Maximizing reward values modelled by human/LLM preference data;
  - Practices: RLHF, Direct Preference Optimization…

- Multi-objective (MO) Alignment
  - Fact: Heterogeneous human expectations make scalar supervisions inefficient;
  - MO alignment simultaneously aligns multiple objectives (e.g. The 3H goals);
  - Practices: MORLHF, MODPO, RiC…

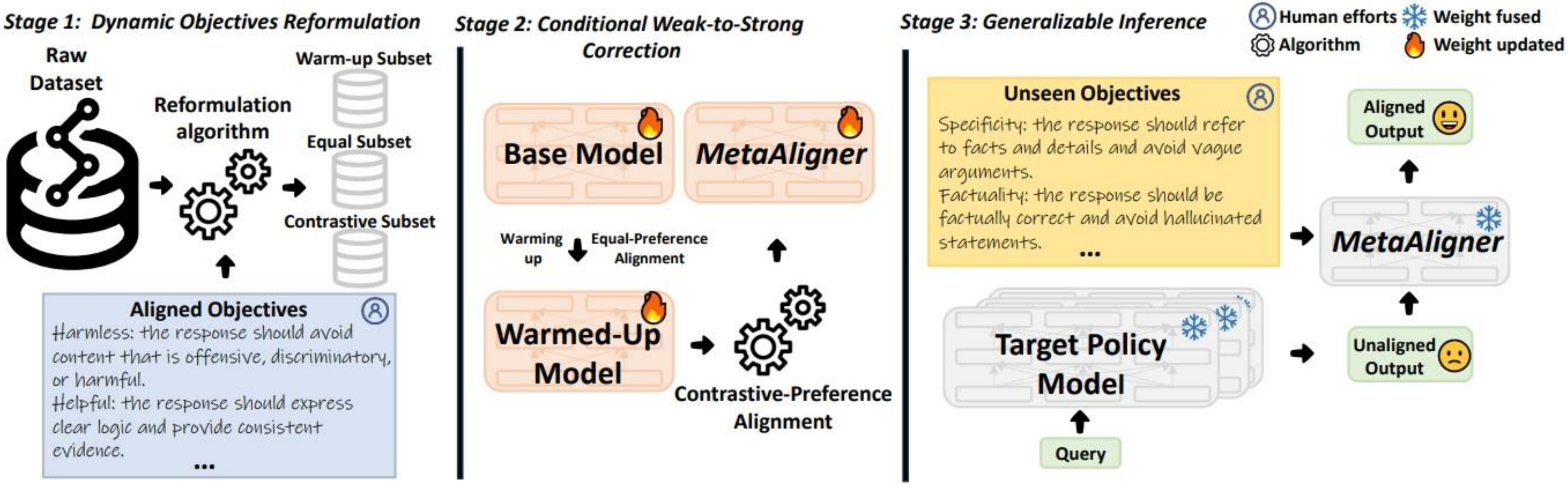
- Current Challenges of MO Alignment
  - Require repetition of high-cost alignment algorithms for each newly-introduced policy model;
  - Poor generalizability
    - Statically aligned on pre-determined objectives;
    - No efforts in expanding and evaluating their capabilities on unseen objectives

MetaAligner

Algorithm	Paradigm	Multi-Objective Alignment	Policy-Agnostic Alignment	Generalizability
RLHF [22]	PPO	✗	✗	✗
MORLHF [19]	PPO	✓	✗	✗
MODPO [10, 39]	SFT, DPO	✓	✗	✗
RiC [35]	SFT	✓	✗	✗
Aligner [12]	SFT	✗	✓	✗
MetaAligner	SFT	✓	✓	✓

- MetaAligner: the first policy-agnostic and generalizable method for multi-objective preference alignment
    - **Dynamic objectives reformulation** algorithm reorganizes traditional alignment datasets into dynamic-objective alignment dataset;
    - **Conditional weak-to-strong correction** aligns the weak outputs of policy models to approach strong output;
    - **Generalizable inference** flexibly adjusts target objectives by updating their text descriptions in the prompts.

Model Overview



Dynamic Objectives Reformulation

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Algorithm 1 Dynamic objectives reformulation.

Require: Raw dataset $D_m : \{q_i, y_{i1}, y_{i2}, P_i\}_{i=1}^{m}$;
Objective text descriptions: $[\langle d_1 \rangle, ..., \langle d_N \rangle]$;
Prompting template: $\mathcal{T}(q, y, \mathcal{O}, t)$
Ensure: Contrastive subset $\mathcal{D}_c$; Equal subset $\mathcal{D}_e$.
$\mathcal{D}_c \leftarrow \varnothing, \mathcal{D}_e \leftarrow \varnothing$ ▷ Initialize the 2 subsets.
for $i \in \{1, ..., m\}$ **do** ▷ Loop on instances.
  $\mathcal{O}_{\succ} \leftarrow \varnothing, \mathcal{O}_{\prec} \leftarrow \varnothing, \mathcal{O}_{\equiv} \leftarrow \varnothing$
  for $j \in \{1, ..., N\}$ **do**
    if p_{ij} is $\succ$ **then** ▷ Collect the objectives where y_{i1} outperforms y_{i2}.
      $\mathcal{O}_{\succ} \leftarrow \mathcal{O}_{\succ} \cup \{\langle d_j \rangle\}$
    else if p_{ij} is $\prec$ **then** ▷ Collect the objectives where y_{i2} outperforms y_{i1}.
      $\mathcal{O}_{\prec} \leftarrow \mathcal{O}_{\prec} \cup \{\langle d_j \rangle\}$
    else ▷ Collect the objectives where y_1 and y_2 performs equally.
      $\mathcal{O}_{\equiv} \leftarrow \mathcal{O}_{\equiv} \cup \{\langle d_j \rangle\}$
    end if
  end for
  if $\mathcal{O}_{\succ} \neq \varnothing$ **then**▷ Build the training pairs where y_{i1} is used as the target.
    $t \leftarrow$ *better*
    $\mathcal{O}_{\succ} \leftarrow$ *random_shuffle*$(\mathcal{O}_{\succ})$
    $\mathcal{D}_c \leftarrow \mathcal{D}_c \cup \{(\mathcal{T}(q_i, y_{i2}, \mathcal{O}_{\succ}, t), y_{i1})\}$
  end if
  if $\mathcal{O}_{\prec} \neq \varnothing$ **then**▷ Build the training pairs where y_{i2} is used as the target.
    $t \leftarrow$ *better*
    $\mathcal{O}_{\prec} \leftarrow$ *random_shuffle*$(\mathcal{O}_{\prec})$
    $\mathcal{D}_c \leftarrow \mathcal{D}_c \cup \{(\mathcal{T}(q_i, y_{i1}, \mathcal{O}_{\prec}, t), y_{i2})\}$
  end if
  if $\mathcal{O}_{\equiv} \neq \varnothing$ **then**▷ Build equally-preferred training pairs.
    $t \leftarrow$ *equal*
    $\mathcal{O}_{\equiv} \leftarrow$ *random_shuffle*$(\mathcal{O}_{\equiv})$
    $\mathcal{D}_e \leftarrow \mathcal{D}_e \cup \{(\mathcal{T}(q_i, y_{i2}, \mathcal{O}_{\equiv}, t), y_{i1})\}$
  end if
end for

- Construct a dynamic multi-objective dataset;
  - Triggers MetaAligner's ability for flexible adjustment of alignment objectives.
- We use the following prompting template:

[$\mathcal{T}(q, y, \mathcal{O}, t)$] Edit the following Question-Answer pair to make it $\{t\}$ considering the following objectives $\{\mathcal{O}\}$ | Question: $\{q\}$ | Answer: $\{y\}$ | Edit:

- Advantages:
  - Instance-level alternation of the target objectives enables flexible alignment;
  - Mutual alignment fully leverages the supervision information;
  - Reward-free alignment avoids complicated preference-to-reward mapping.

Conditional Weak-to-Strong Correction

- An SFT-based training objective:

$$\underset{\theta}{argmin} -\mathbb{E}_{(q,y_0,y,\mathcal{O})\sim\mathcal{D}}\left[log\, \delta_\theta(y|\mathcal{T}(q,y_0,\mathcal{O},t))\right]$$

  - Advantages:
    - Computation resources is detached from policy model size;
    - Works via policy model outputs, allowing training and inference on close-source policy models.

- Three-step Model Training:
  - Warming up;
  - Equal-preference alignment;
  - Contrastive-preference alignment.

Generalizable Inference

- Manipulate the target objectives by adjusting combinations of text descriptions in the objective set.

$$\mathcal{O} = \langle d_3 \rangle; \langle d_1 \rangle; \langle d_4 \rangle$$

- **Flexible adjustment of text descriptions for existing objectives and injections of unseen objectives.**

$$\mathcal{O}^* = \langle d_3 \rangle; \langle d_1 \rangle; \langle d_4 \rangle; \langle d_5^* \rangle; \langle d_6^* \rangle$$

Experimental Results

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Table 2: Performance of *MetaAligner*-(1.1B, 7B, 13B) on 3 datasets over different policy models. The responses are simultaneously aligned on all trained objectives, then evaluated on each objective. "IF" denotes the "Instruction following" objective. "+" shows the advantage of aligned outputs over the unaligned outputs on win rates against the ground-truth responses.

		HH-RLHF			UltraFeedback				IMHI		
MetaAligner	**Policy Model**	**Harmless**	**Helpful**	**Humor**	**IF**	**Honest**	**Truthful**	**Helpful**	**Correct**	**Informative**	**Professional**
1.1B	LLaMA2-Chat-7B	+10.0%	**+20.0%**	+14.75%	+11.0%	+15.0%	+14.33%	+9.0%	+18.33%	+20.55%	+31.67%
	LLaMA2-Chat-13B	+10.75%	+9.08%	+13.25%	+8.66%	**+15.34%**	**+16.33%**	+7.67%	+11.11%	+8.33%	+25.0%
	LLaMA2-Chat-70B	+6.58%	+7.42%	+22.58%	+6.0%	+12.67%	+17.33%	+16.33%	+8.33%	+14.23%	+17.23%
	Gemma-instruct-2B	+8.5%	+12.25%	+12.33%	**+14.67%**	+14.67%	+13.0%	+5.33%	15.55%	**+35.55%**	**+37.23%**
	Gemma-instruct-7B	+4.0%	+7.75%	+23.17%	+9.0%	+10.0%	+4.67%	**+14.0%**	**+18.9%**	+31.12%	+36.11%
	Vicuna-7B	**+11.5%**	+10.83%	+20.33%	+11.33%	+13.33%	+12.33%	+7.0%	+10.0%	+7.22%	+6.33%
	Vicuna-13B	+7.42%	+13.0%	+19.17%	+11.66%	+14.34%	+15.33%	+10.0%	+12.22%	+7.78%	+3.34%
	Vicuna-33B	+8.5%	+2.59%	**+23.83%**	+8.0%	+11.67%	+6.33%	+6.67%	+8.34%	+4.44%	+6.12%
	GPT-3.5-Turbo	+1.42%	+7.5%	+17.84%	+5.0%	+5.0%	+3.66%	+1.0%	+9.67%	+1.33%	+9.33%
	Claude-3-Sonnet	-3.83%	+1.58%	+13.17%	+4.67%	+2.67%	+2.67%	+3.0%	+7.0%	+2.33%	+6.66%
7B	LLaMA2-Chat-7B	+25.0%	**+27.0%**	+20.75%	+34.66%	+36.0%	+37.0%	+28.0%	+21.67%	+32.22%	+43.89%
	LLaMA2-Chat-13B	**+28.75%**	+20.58%	+18.25%	34.0%	+37.34%	+37.66%	+23.3%	+25.56%	+30.0%	+33.89%
	LLaMA2-Chat-70B	+16.58%	+14.42%	+29.08%	+31.0%	+27.0%	+31.33%	+17.0%	+20.56%	+17.23%	+21.67%
	Gemma-instruct-2B	+20.0%	+18.75%	+17.83%	**+41.33%**	**+40.67%**	**+42.33%**	+31.33%	+25.0%	+50.55%	+51.67%
	Gemma-instruct-7B	+11.0%	+23.25%	+26.67%	+33.67%	+35.34%	+31.0%	+29.0%	**+35.01%**	**+52.23%**	**+56.11%**
	Vicuna-7B	+19.5%	+18.83%	+27.33%	+38.0%	+39.0%	+37.0%	+32.33%	+23.33%	+22.78%	+23.33%
	Vicuna-13B	+14.92%	+21.0%	+30.67%	+34.66%	+40.0%	+39.67%	**+36.34%**	+25.55%	+20.0%	+15.01%
	Vicuna-33B	+28.0%	+17.09%	**+30.83%**	+30.0%	+37.34%	+32.33%	+29.33%	+11.11%	+16.11%	+8.34%
	GPT-3.5-Turbo	+15.92%	+21.5%	+22.84%	+29.99%	+30.34%	+28.0%	+14.34%	+18.67%	+16.33%	+14.22%
	Claude-3-Sonnet	+19.17%	+19.08%	+26.17%	+22.33%	+21.0%	+21.67%	+19.0%	+11.33%	+19.33%	+11.33%
13B	LLaMA2-Chat-7B	+24.0%	**+30.5%**	+23.75%	+51.83%	+47.5%	+45.33%	+38.67%	+28.33%	+38.33%	+50.56%
	LLaMA2-Chat-13B	+17.75%	+16.58%	+15.75%	+46.33%	+48.67%	+46.83%	**+41.17%**	+30.56%	+37.22%	+40.56%
	LLaMA2-Chat-70B	+16.58%	+19.42%	+26.58%	+44.33%	+35.0%	+45.5%	+24.0%	+31.67%	+30.56%	+36.12%
	Gemma-instruct-2B	+18.5%	+17.25%	+24.33%	**+55.0%**	+44.67%	**+51.33%**	+36.83%	**+35.55%**	**+63.33%**	**+65.0%**
	Gemma-instruct-7B	+17.5%	+23.75%	+30.17%	+42.0%	+40.17%	+35.17%	+31.17%	+34.45%	+50.0%	+49.44%
	Vicuna-7B	+19.0%	+19.83%	+26.33%	+41.5%	+39.83%	+44.33%	+37.5%	+24.44%	+23.33%	+21.11%
	Vicuna-13B	+18.92%	+28.5%	**+32.67%**	+47.33%	+49.17%	+47.0%	+40.67%	+28.33%	+23.34%	+18.9%
	Vicuna-33B	**+31.5%**	+20.09%	+27.83%	+50.5%	**+53.17%**	+45.83%	+38.5%	+23.89%	+23.89%	+14.45%
	GPT-3.5-Turbo	+18.42%	+25.0%	+29.34%	+40.33%	+40.17%	+36.83%	+23.67%	+26.67%	+25.66%	+33.62%
	Claude-3-Sonnet	+21.17%	+20.58%	+27.17%	+38.5%	+39.5%	+37.67%	+29.83%	+28.67%	+20.0%	+11.2%

Experimental Results

Table 3: Comparisons of win rates between alignment methods. "GPU Hours" records the summed GPU running time on all datasets. "-Equal Pref." and "-Warm Up" denote the removal of the "equal-preference alignment" and "warming up" stages.

Policy Model	Algorithm	GPU Hours	HH-RLHF Harmless	HH-RLHF Helpful	HH-RLHF Humour	HH-RLHF Avg.	UltraFeedback IF	UltraFeedback Honest	UltraFeedback Truthful	UltraFeedback Helpful	UltraFeedback Avg.
LLaMA2-Chat-7B	MORLHF	1892.3	62.83%	51.2%	77.5%	63.84%	32.18%	33.7%	26.1%	33.7%	31.42%
	MODPO	405.9	65.0%	64.0%	78.0%	69.0%	30.82%	43.4%	37.19%	25.0%	34.1%
	SFT	247.34	66.5%	75.0%	76.5%	72.67%	27.0%	36.5%	26.0%	36.5%	31.5%
	Aligner-7B	236.8	72.0%	81.9%	70.12%	74.67%	52.38%	44.23%	37.19%	39.1%	43.23%
	MetaAligner-1.1B	120.48	62.5%	75.0%	77.0%	71.5%	27.67%	27.0%	33.0%	25.33%	28.25%
	MetaAligner-7B	242.68	**77.5%**	82.0%	83.0%	80.83%	51.33%	48.0%	55.67%	44.33%	49.83%
	-Equal Pref.	–	73.82%	80.7%	77.39%	77.3%	46.8%	43.6%	53.17%	41.7%	46.32%
	-Warm Up	–	77.1%	80.32%	82.63%	80.02%	49.96%	47.4%	55.73%	44.18%	49.32%
	MetaAligner-13B	403.44	76.5%	**85.5%**	**86.0%**	**82.67%**	**68.5%**	**59.5%**	**64.0%**	**55.0%**	**61.75%**
LLaMA2-Chat-70B	Self-Refinement	–	70.48%	82.8%	68.91%	74.06%	49.95%	62.91%	60.77%	**57.6%**	55.05%
	MetaAligner-7B	242.68	**85.16%**	**89.42%**	**88.08%**	**87.55%**	**67.05%**	**63.72%**	**70.1%**	54.7%	**63.89%**

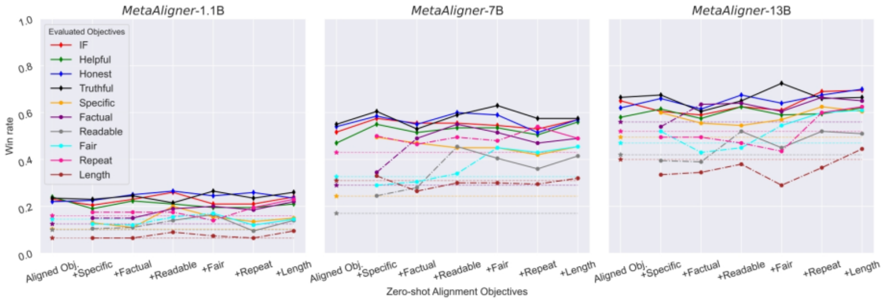

Figure 3: Zero-shot alignment on 6 unseen objectives. In the x-axis, "Aligned Obj." denotes the 4 supervised objectives ("◇" markers), and "+" denotes *further* addition of an unseen objective ("○" markers). "⋆" denotes the win rates for the unseen objectives before all zero-shot alignments, "-." lines identify win rate fluctuations before alignment, and solid lines identify fluctuations after alignment.